Case Study on Intelligent Factory Systems for Improving Productivity and Capability in Industry 4.0 with Generative AI

Reeta Parmar
Computer Science and Engineering
St. Andrews Institute of Technology and Management, Gurgaon
Haryana, India
reetathakur1988@gmail.com

Sanchali Kapoor
Management
St. Andrews Institute of Technology and Management, Gurgaon
Haryana, India
sanchali.kapoor@gmail.com

Sidra Saifi
Bacholer of Computer Applications
St. Andrews Institute of Technology and Management, Gurgaon
Haryana, India
uhm.sidraaaa@gmail.com

Puneet Garg
Computer Science and Engineering
KIET Group of Institutions, Delhi NCR, Ghaziabad, India
puneetgarg.research@gmail.com

***Abstract*— Industry 4.0 is the next generation of automation in manufacturing with rapid development affecting manufacturing to intelligent technologies data driven-decision making. Intelligent Factory Systems (IFS) incorporate the latest trends including IoT, cyber-physical systems and Generative AI for productivity gains as well operational excellence. This case study illustrates how Generative AI accelerate manufacturing as it offers seamless process automation, predictive maintenance and responsive production ability. Integrating AI derived insights will enable factories to operate in real-time optimization mode, decrease downtime and boost crew collaboration across the enterprise. This research showcases field-level implementations where production rates have increased and operational costs have decreased with the adoption of AI-driven intelligent systems onto manufacturing equipment resulting in overall equipment effectiveness (OEE) improvements. It also looks at issues, like cybersecurity, data quality and the labor shift from doing to explaining via AI. The study is useful in understanding how manufacturers can use Generative AI to innovate and differentiate in the changing Industry 4.0 competitive landscape.**

Keywords*— Generative AI in Manufacturing, Industry 4.0 Automation, Intelligent Factory Systems (IFS), AI-Driven Process Optimization and Operational Excellence through IoT and AI.

I. INTRODUCTION TO INTELLIGENT FACTORY SYSTEMS

Intelligent Factory Systems allows the merged terms systems of automation, artificial intelligence (AI), the internet of things (IOT), and data analysis into making smart, lean with productivity within manufacturing environments [13]. They leverage real-time data, predictive analytics and self-learning to improve production processes, cut down expenses and improve product quality [25]. Intelligent factories are part of Industry 4.0 goal of realizing a digital transformation that enables machines, systems and humans to communicate seamlessly [4].

A. Overview of Industry 4.0 and Smart Manufacturing

Industry 4.0, also called the Fourth Industrial Revolution, is a transformation from conventional industrial processes to digitized and automated connections, connected and AI-controlled manufacturing systems [7]. The Smart manufacturing which is the single key of purpose in Industry 4.0 is:

- **Cyber-Physical Systems (CPS):** The marriage of physical machines into digital models for real-time tracking and tweaking [19].
- **Internet of Things (IoT):** Sensors/devices are on the factory floor to connect and share data along the manufacturing process [10] [20].
- **Big Data and Analytics:** Machine Learning insights to scale operations better, predict maintenance etc. from large sets of data [10] [27].
- **Digital Twins (Digital Twin):** A digital replica of physical systems that is capable of simulation, modelling and real-time manipulation [7].
- **Cloud Computing:** Centralized to enable you access and enhance decision-making by consolidating data [1] [21].
- **Autonomous Robots:** AI-powered robots increase efficiency and quality of production while scaling capabilities.

B. Role of Generative AI in Modern Factories

Generative AI reinvents modern factories, as it integrates advanced automation, smart decision making and new design process into operations. Some Core Roles of Generative AI in manufacturing are:

Figure1: Generative AI in Modern Factories

- **Product Design and Optimization:** Generative AI builds thousands of solutions at the same time to various design-based problems using large dataset and they can be used for rapid generation of alternative design solutions [16]. This approach yields lean products able to pass performance requirements coupled with less material usage and faster

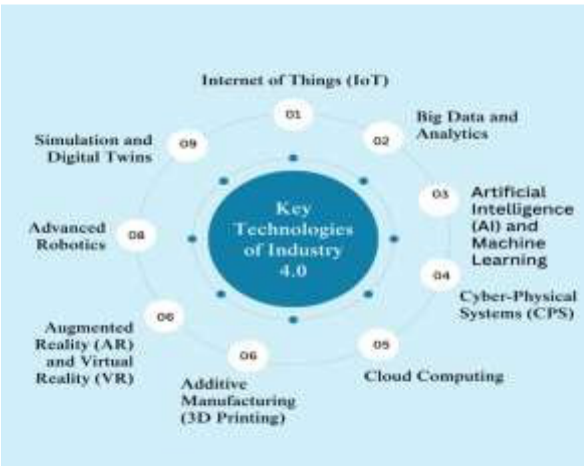
ISBN: 978-93-343-1044-3

time-to-market. As an example: AI may propose design changes for improvement of strength, whilst keeping the weight low -critical in industries like aerospace or automotive.

- **Process Automation and Predictive Maintenance:** In manufacturing, generative AI helps with process automation through data driven equipment failure prediction and proactive maintenance by learning from past [3]. Predictive maintenance keeps unplanned downtimes low and allows machinery to last longer [6]. Using AI to check sensor data, identify anomalies and suggest necessary treatments ensure smooth and real time functioning.
- **Quality Assurance:** Generative AI, quality assurance It analyses production data to detect patterns of defect with generative AI Step 2 In order to catch these patterns at a very early stage, the manufacturers can take corrective actions before failures and hence, deliver good quality products [6]. This preventative method is to eliminate waste, decrease expenses and preserve customer delight.
- **Training and Skill Development:** Generative AI workforce development supporting customized training by enrollments system. It can do like a simulation of real-world scenario to act as a hands on in controlled environment. Such method aids in short term of learning and enhancing the rate of skill development/ automation readiness for employees to operate next gen manufacturing systems [12].
- **Supply Chain and Logistics Optimization:** Through the consumption of large data using Generative AI — to predict demand, adjust inventory and route after-sales logistics [2]. It enables manufacturers to test different supply chain hypotheses and strategies for avoiding bottlenecks in the future with simulations. Which results in a lower cost, prompt delivery time and the ability to better adapt market changes.

II. UNDERSTANDING INDUSTRY 4.0 AND ITS KEY TECHNOLOGIES

The Industrial Revolution/Industry 4.0 is a revolution in manufacturing fueled by the digital integration of production assets [2]. The transition seeks to build smart factories that are more efficient, adaptable and market-in tune [16]. Some of the major technologies responsible for this transformation are:



- **Internet of Things (IoT)**: IoT is process of connecting machines/devices/sensors on Internet, thereby helps to exchange data in real time and communication [11]. IoT allows for monitoring and control of equipment in manufacturing that drives efficiency as well predictive maintenance [18] [19].
- **Big Data and Analytics**: There is a lot of data from devices connected being analyzed to analyses the manufacturing processes [20]. Big Data analytics provides patterns to boost the operation and policy-oriented decisions improving productivity [14].
- **Artificial Intelligence (AI) and Machine Learning**: AI, machine learning algorithms allow machines to learn from data, recognize new inputs and perform tasks which often need human intelligence [11] [27]. AI implemented in manufacturing for quality assurance, predictive maintenance and process optimization [19].
- **Cyber-Physical Systems (CPS)**: combines computation, networking and physical processes Together in an integrated engineering design CPS means computation, network and the physical system. They enable the generation of digital twins industrialize physical assets so they can be simulated for analysis to simulate behavior [9].
- **Cloud Computing**: Cloud platforms offer a lot of scalable computing resources and storage [1], which are able to help manufacturers with their data management/storage & analysis on day without having the on-premise infrastructure [21]. Which helps to work together, share of information between locations.
- **Additive Manufacturing (3D Printing)**: Through additive manufacturing, one can build complex structures part by layer material addition [12]. This technology facilitates rapid prototyping and increases customization/also lower material wastage.
- **Augmented Reality (AR) and Virtual Reality (VR)**: AR & VR technologies provides engaging experiences that can be utilized for training, maintenance and also design visualization [14]. AR may superimpose digital information on top of physical equipment to walk workers through intricate procedures.
- **Advanced Robotics**: Modern day robots are more flexible and can work side by side with human workers performing complex tasks. Compared to primary automation they increase productivity and can be retooled for various tasks to give extended manufacturing flexibility [12].
- **Simulation and Digital Twins**: Manufacturers can use simulation tools and digital twins to simulate / analyze production processes in a virtual setting [6]. So that the processes can be optimized and experimented in a simulated space prior to physical implementation.

III. GENERATIVE AI IN SMART MANUFACTURING

Generative AI is transforming Smart manufacturing with intelligent automation, data enabled decision making and the adaptive process optimization [3]. Generative AI, unlike conventional AI that mainly reviews the past data For example some of the real use case in manufacturing drives manufacturing effectiveness, output and innovation because new data or simulations or predictive models from next level manufacturing is created [14]. It enable real-time problem solving, process automation and enhanced factory operations by providing the views that further enhance design of manufacturing and quality control.

A. *Concept and Applications of Generative AI in Factories*

ISBN: 978-93-343-1044-3

In smart factories, Generative AI works by foraging over these large datasets to come up new solutions to industrial problems [5]. Some of the important applications are:

- **Product Design and Optimization:** Generative AI Develops the design optimized products using performance requirements, material constraints into cost efficient structure [16]. It speeds up prototyping with respect to many design iterations and allows you develop quickly, produce less for the same time.
- **Predictive Maintenance** – You are able to run your machines on real time machine health by the AI models to predict the failure beforehand [3]. These de-clutters unplanned downtime, decreases maintenance expenses and assets life expectancy
- **AI- based Automated Quality Control —** The defect detection of generative AI is analyzed with images and sensor data It can also automate product quality improvements without human interference if necessary potential improvements to processes [12]**.**
- **Supply Chain Optimization –** AI models will tune inventory levels, logistics and demand forecasting for the leanest supply chain that remains responsive with the consumers [2].
- **Digital Twins of the factory (AI generated virtual factory model)** — Using process simulation & digital twins for real-world manufacturing environment allows manufacturers to evaluate changes in processes before implementations [6].
-

B. AI-Driven Decision Making and Process Optimization

Generative AI: Learn by real-time data for actionable insights Generative AI Enhances Decision Making Some of its key contributions are:

- **In-Production Real-Time Adjustments** – AI is monitoring and tweaking production settings in real-time, saving time & money as well as waste.
- **AI and energy management** — Machine learning systems observe how much energy is used for various activities and suggest a way to use less power reducing costs as well as the toll on the environment [6].
- **Dynamic Workforce Allocation**: AI identifies the right distribution of the workforce to make sure your skilled personnel are doing essential work there by avoiding over-usage of a resource if it requires assistance in some another places for skill qualifications [3].
- **Anomaly Detection & Risk Mitigation** – Change the way managers think, by providing anomalies in production process to them before it gets worse [15].

IV. CHALLENGES IN TRADITIONAL MANUFACTURING SYSTEMS

The traditional manufacturing systems are based on linear, inflexible and labor-intensive processes that rarely satisfy the needs of contemporary data driven automated Industry 4.0 environments to meet Industry 4.0 requirements [4]. These systems have been designed with limitations such as inefficiencies and high operational expenses, limited data utilization and not very flexible [3]. In the emerging era of intelligent factory systems, the conventional approach is going to work against traditional methods (if it is not dropped already) as industries move to new age.

A. Limitations of Conventional Production Approaches

- **No Real-Time Data based Decision Making***:* Manufacturing systems are the best traditional ones and they utilize real time analytics as end-product of decision making therefore sticking further to delays just to figure it out later What the production bottlenecks, machine break down and quality defect explain not aim full but respond [4].
- **High Reliance on Manual Operations***:* Manually operated many traditional factories will make any sudden noise (Audio), the series of human can occur another errors / wastages / discrepancies [7]. Scale issues labor heavy processes do come across in preparing for purpose and are expensive to scale
- **Limited Tailoring and Flexibility***:* Mass production (traditional manufacturing systems are made for mass production and thus can't hold customized or small batch manufacturing very well). Adjusting Mass manufacture original production systems are adjusted without much hustle for personalized or small batch manufacturing [12]. It requires a lot of production line reconfigurations to be able to cater to market changes which reduces the agility.
- **Resource Not Optimized Efficiently***:* High energy consumption, over material wastage and under optimized supply chains which are making operating costs shoot up [6]. Conventional systems have no predictive maintenance, those systems tend to break down quite often and put your operations down.
- **Lack of integration between advanced technologies***:* Most smart factories work in a soloed structure; getting AI, IoT, robotic and digital twins into the existing workflows can be quite difficult [2] [22]. Issues with Interoperability When Moving towards Smart Manufacturing in Legacy systems [12].

B. Barriers to Implementing Intelligent Factory Systems

Introducing Intelligent Factory Systems (IFS) that implement IoT, AI, automation and big data for manufacturing is difficult in presence of multiple barriers [24]. So here are the key hurdles:

ISBN: 978-93-343-1044-3

- **High capex investment** – upgrading intelligences requires high costs for new equipment, sensors and AI processes [17].
- **Current legacy systems Integration** – a lot of industries are still running business on ageing systems and hence integration with new technology complex & costly [13]**.**
- **Cyber Security** — the more connected the factory gets, the more it exposes itself to cyber threats and needs a strong cybersecurity [28].
- **Insufficient Talent Pool** — AI requires the use of data science, IoT and automation to much more expertise, leading to talent shortage [12].
- **Data Privacy & Ownership**– The management of vast amount of Industrial data is extremely tricky because industrial data is sensitive and highly regulated.
- **Operational Disruptions** – Going to intelligent system might result in some temporary impact in your manufacturing productivity and operations.
- **Scalability Concerns** – Propagating smart factory solutions across multiple sites is tricky because the infrastructure is different [2].

V. CASE STUDY OVERVIEW: IMPLEMENTATION OF INTELLIGENT FACTORY SYSTEMS

Introducing Intelligent Factory Systems (IFS) in the industry 4.0 context stands as a ground-breaking method of manufacturing using synergy of technologies like IoT, AI and cyber-physical systems to enable smart, efficient and scalable production facilities [7] [11].

A. Objectives and Scope of the Study

The primary objectives of this case study are to:

- **The Enabling Journey of Intelligent Factory Systems**: Look into how the intelligent factory systems are implemented in a manufacturing process [17].
- **Look at Technology Feeding**: Examine the extent how state of the art technologies (Cyber-Physical Systems (CPS), Internet of Things (IoT) and Artificial Intelligence (AI)) are fed within today existing manufacturing models [23].
- **Operational efficiency impacts of Smart systems** (Production efficiency, product quality and Operational performance overall) [3].
- **Issues and Solutions**: Point out the challenges that were run into and how that you managed in effectively overcoming them

The scope of this study encompasses:

- **Technological Setup**: A smart factory architecture built on IoT object layers, a CPS network layers and a CPS service layer that can link the shop floor of the cloud services in deployment [4] [21].
- **Process Optimization**: Lean manufacturing principles and intelligent systems to improve the production processes in place
- **DATA ANALYSIS / Real-time** data collection & analytics to drive faster/what-if decision making and predictive maintenance [5] .

B. Selection of Industry and Manufacturing Setup

The automotive manufacturing industry is a good example of the study; it is one complex production process with massive need for accuracy and extensive personalization [10]. This manufacturing setup has been chosen to be a plant involved in automotive parts production, such as batteries, motors, electronic control unit based on electric vehicle [13]. Here, we offer a broad base to measure the influence of IFS on manufacturing as applied to assembly-line efficiency or supply chain myriad.

VI. AI-Powered Innovations in Intelligent Factories

AI and Industry 4.0 It is a fact that AI-powered innovations will drive huge transformation from conventional manufacturing to intelligent factory systems in the industry 4.0. Some key developments are:

A. Predictive Maintenance and Anomaly Detection

It is to monitor machinery in real-time with data on temperature, vibration and pressure thus forecast pending failures with help of AI. Early detection of anomalies can lead to planned maintenance, leading to minimized unplanned downtimes and prolonging lifespan of equipment [5]. AI, for example; goes through data from jet engines hydraulic systems and even landing gear to find anomalies early providing that maintenance can be scheduled during normal ground times hence to minimize flight schedule disruptions.

B. AI-Based Quality Control and Defect Prediction

AI in quality control processes will be able to improve defect detection and prevention. Machine learning models on the factory floor digest massive production data tables for when things start going wrong so that manufacturers can fix what turns defects are not acceptable when they are manufactured [11]. This forecasting provides a way to reduce waste and maximize the yield. What we mean is that AI-based systems look for defects with an ability that goes beyond observing defects that exist, they can predict future location and time of defects to come thereby enabling immediate waste minimization and yield optimization [5].

C. Autonomous Supply Chain and Logistics Optimization

ISBN: 978-93-343-1044-3

AI helps to automate and improve supply chain process. AI can leverage data from the end-to-end supply chain allowing for forecasting demand variances, inventory optimization and more efficient route planning in logistics [3]. This results to better productivity and lower cost as well as speeding up delivery. AI can also suggest several possibilities and options to augment processes like managing risks, allocative resource distribution etc. thus shaping a more efficient and flexible supply chain.

VII. ENHANCING PRODUCTIVITY THROUGH INTELLIGENT AUTOMATION

Intelligent Automation is changing manufacturing by incorporating advanced technologies for increased productivity automation and efficiency. Main areas are:

A. AI-Enabled Human-Robot Collaboration

Human-Robot Collaboration (HRC) in the contemporary manufacturing Human adaptability with robotic precision. Both, robots (collaborative robots) working in tandem with humans to perform tasks thus increasing the efficiency of production [5]. Embedded AI broadens this symbiotic relationship by allowing the robot to interpret and act upon human behavior for a means of both safety & productivity. AI is used by in the form of robots where for example AI enabled robots are trained to learn from human behavior and get more natural interactions or task completion [16].

B. Dynamic Workflow Optimization in Manufacturing

Dynamic optimization of workflow with AI the real-time data from all of your manufacturing processes are fed into these algorithms to diagnose any inefficiencies and suggest changes [14]. Production scheduling; resource leveling and the ability to predict maintenance moments means less downtime, better throughput all AI-driven systems. These systems learn from the operational data in real-time to allow for situational, optimal performance.

VIII. Improving Capability with Generative AI

Combining Generative AI and Adaptive Learning into manufacturing systems can give a significant amount more of design optimization not as well as operational enhancement [13].

A. Generative AI in Design Optimization

Generative AI uses complex algorithms to freely produce large number of design alternatives within those parameters and constraints using some form user input [5]. Manufacturers stand to gain a lot of benefits from this capability in the field of manufacturing as follows:

- New Design Concepts: Generative AI will be capable of exploring a lot of design space thus may be able to propose solutions which a human designer would not immediately come up with [1]. For example, generative AI with additive manufacturing (3D printing) can produce intricate and individual parts with optimized material usage and performance.
- Improved efficiency: The technology can design for specific targets or metrics like weight save, stiffness increase or aerodynamics performance which result in a better performance product [3]. For example, generative AI could propose the most efficient manufacturing processes (machine settings) for a standard part
- Sustainability: Generative AI reduces material waste in the manufacturing process and design optimization, which results in less waste and hence less material usage [15]. This also improves the energy efficiency and savings so high that it can blow minds.

B. Adaptive Learning for Process Improvement

Systems that self-adjust to real-time data and feedback, enabling some manufacturing process continuous improvements via Adaptive Learning [13]:

- **Optimize Production as a Process in Real Time**: Adaptive systems can monitor production conditions & output; they then quickly adjust to keep the process running close to optimal [2]. Adaptive manufacturing for example where manufacturers are able to adapt their production remotely by keeping an eye on it and adjusting real-time based on indicators similar automated systems.
- **Personalized Employee Training** — Adaptive learning platforms appreciate employee needs in training programs ensuring that employees are up-to date and familiar with the newest technology/processes [11]. It drives efficiency and diminishes mistakes to some level.
- **Continuous Improvement** – Adaptive learning is more about continuous improvement as in company is focused on small steps of learning where companies try get better than their past/decision and refine these by incremental change [16].

IX. MEASURING SUCCESS: KEY PERFORMANCE INDICATORS (KPIS)

Assessment of succeed using intelligent factory systems entails tracking down some Key Performance Indicators (KPIs) which align with productivity efficiencies improved efficiency enhancements cost savings and return on investment (ROI) [11].

A. Productivity Metrics and Efficiency Gains

To assess productivity and efficiency in manufacturing, consider the following KPIs:

- **Overall Equipment Effectiveness [OEE]:** OEE is how well manufacturing equipment is being utilized, measured for availability, performance and quality [2]. A perfect production rate of 100 % means that only good parts are being manufactured as fast as possible but no downtime.
- **Throughput:** this is the total amount of output generated in given period of time [12]. Tracking throughput aids in the identification of key production bottlenecks and potential process improvement opportunities.
- **First Time Yield (FTY):** FTY measures the percentage of products manufactured right the first time, and no reworks required a higher FTY signifies effective processes and better-quality control [3].

B. Cost Reduction and ROI Analysis

ISBN: 978-93-343-1044-3

To evaluate the financial impact of intelligent automation on organization, one needs to look at savings / ROI using these metrics:

- **Cost Savings**: Quantify labor and material, as well as operational savings from automation Calculate automation benefits on labor hour's material costs & overall operational expenses [5]. The implementation of a customized system for example may help in reducing operational cost by minimizing labor and manual intervention massively.
- **Savings in Time**: Quantify time saved as a result of automation when doing the tasks (of course it can vary depending on automation level). Savings in time equals more capacity and the willingness to accept extra loads without adverse corresponding cost increases [3].
- **Reduction in Mistake**: Measure the reduction of errors and the cost associated with those errors due to automation [2]. Fewer errors equate to higher quality products and decrease rework and scrap costs.
- **Return on investment (ROI):** Measure the financial returns that automation brings compared to the investment made us have a Positive ROI: Automation has More Value than the cost [2].

X. CHALLENGES AND FUTURE PROSPECTS OF AI-DRIVEN FACTORIES

Artificial intelligence (AI) in manufacturing: great strides, but challenges and ethical considerations that need mitigation for responsible and secured adoption [1] [7].

A. Ethical and Security Concerns in AI Manufacturing

AI manufacturing needs data and lots of it as well (including proprietary info and personal employee data). Proper Data Protection is essential, to stop breaches and presentments from happening [12].

- **Algorithmic Bias and Fairness**: Whether designed by humans or replicating human biases, AI algorithms invariably introduce unfairness that can degrade the quality of products created and workplace equity [1]. For the sake of AI fairness, this is to say we need to figure out how we can detect bias and fix it in models [11].
- **Transparency and Accountability**: AI in some decision-making processes is not transparent and, therefore, accountability for actions take away from the system [3]. Explainable AI systems need to be developed so that the decisions are verifiable and justifiable from an auditing perspective.
- **Displacement of Employment**: AI used to automate tasks which will cause displacement of workforce. A good mix of technology ambition with re-training and up skilling strategies to minimize lay-offs [3].

B. Future Trends in Industry 5.0

Industry 5.0 will be the next vertical of industrial evolution, focused on solutions with human in the middle and sustainable development [6]. Key trends are:

- **Human-Robot collaboration**: Collaborative robotics (cobots) collaborate with humans in order to produce safe as well as more productive [3]. These cobots are made to work in collaboration with humans, not as a replacement for them, with the intention that we will have a symbiotic work place.
- **Mass Personalization**: use AI and further manufacturing technologies to have personalized products that are customized per customer preference instead of mass production as well as mass customization not beyond it [12].
- **Manufacturing sustainability to use environmentally** friendly materials and energy-saving methods to reduce environmental impacts, overall practice in accordance with global sustainability agendas for manufacturing system
- **Smart and Efficient Manufacturing with Advanced Technologies**; Integration of AI, IoT and Big data analytics-based solutions to build smarter [2], more intelligent manufacturing systems, which can respond to changing needs and conditions [26].

XI CONCLUSION

With the introduction of Industry 4.0 advanced manufacturing is being revolutionized via next-gen technologies including IoT, cyber-physical systems and artificial intelligence (AI). Intelligent Factory Systems (IFS) are the embodiment of this transformation as they leverage real-time data and self-sufficient decision making towards process optimization, product quality enhancement and cost reductions on operating expenses. Key enabler for this change is Generative AI; it is reinventing the entire fabric of manufacturing from design to inspection and sorting and all.

Generative AI plays a big role in product design, creating the figure-out-optimized-designs that fulfill specific performance criteria so integrators can get their projects into development sooner and then save material. AI models in process automation analyses sensor data for equipment failure prediction leading to preventive maintenance that contributes in least downtime and hence increases mechanical life. Also, when it comes to supply chain, Generative AI is expected do thunderclaps for demand forecasting and inventory management that further again complex shipping route planning. This collaboration between human and AI-powered systems, or collaborative robots (cobots) yields another level of automation to take care of any repetitive or dangerous task thus enabling the workforce to concentrate on more complex activities.

Real-world examples prove what the power of AI-powered intelligent system is all about. Bosch applied Generative AI to his training synthetic images for automated optical inspection (entire electric motor stator) resulting in a shorter project time frame and better quality of the inspections. Also, GE Appliances has incorporated Generative AI in its SmartHQ app that allows customizing based on the customer ingredients and creating recipes analogous improved user experience with less food wastage.

And yet, challenges remain. With increased connectivity comes more proper Cybersecurity (the protection of sensitive data) for companies to ensure safety and security. Data integrity is essential to the correct predictions and decisions of AI. In addition, the skills needed for effective use of human machine collaboration in an AI-

ISBN: 978-93-343-1044-3

driven operations are extensive and thus the need for training programs will be large for workforce.

By embracing Generative AI manufacturers are able to foster innovation, optimize in real-time and stay relevant in the Industry 4.0 arena like never before. Not only can AI be incorporated into manufacturing to create more productive and operationally efficient processes but it also paves the way for more nimble, adaptive production environments. Statements from the intersection of Generative AI, operations and everything from fast product design to advanced predictive maintenance and supply chain optimization in order to make based strategic decisions. AI enables manufacturers to produce new, high quality products that improve customer experience while at the same time increase profitability. This integration results in higher efficiency, lower cost and shorter time to delivery, so that manufacturers are impacted with Industry 4.0 dynamic.

REFERENCES

1. Ahmed, I., Jeon, G., & Piccialli, F. (2022). From artificial intelligence to explainable artificial intelligence in industry 4.0: a survey on what, how, and where. IEEE Transactions on Industrial Informatics, 18(8), 5031-5042.
2. Bu, L., Zhang, Y., Liu, H., Yuan, X., Guo, J., & Han, S. (2021). An IIoT-driven and AI- enabled framework for smart manufacturing system based on three-terminal collaborative platform. Advanced Engineering Informatics, 50, 101370.
3. Buchmeister, B., Palcic, I., & Ojstersek, R. (2019). Artificial intelligence in manufacturing companies and broader: An overview. DAAAM International Scientific Book, 81-98. Butt, J. (2020). A strategic roadmap for the manufacturing industry to implement industry 4.0. Designs, 4(2), 11.
4. Çınar, Z. M., Abdussalam Nuhu, A., Zeeshan, Q., Korhan, O., Asmael, M., & Safaei, B. (2020). Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0. Sustainability, 12(19), 8211.
5. Gamoura, S. C., Koruca, H. İ., & Urgancı, K. B. (2023, May). Exploring the Transition from “Contextual AI” to “Generative AI” in Management: Cases of ChatGPT and DALL-E 2. In International Symposium on Intelligent Manufacturing and Service Systems (pp. 368- 381). Singapore: Springer Nature Singapore.
6. Huang, Z., Shen, Y., Li, J., Fey, M., & Brecher, C. (2021). A survey on AI-driven digital twins in industry 4.0: Smart manufacturing and advanced robotics. Sensors, 21(19), 6340.
7. Jagatheesaperumal, S. K., Rahouti, M., Ahmad, K., Al-Fuqaha, A., & Guizani, M. (2021). The duo of artificial intelligence and big data for industry 4.0: Applications, techniques, challenges, and future research directions. IEEE Internet of Things Journal, 9(15), 12861-12885.
8. Jimeno-Morenilla, A., Azariadis, P., Molina-Carmona, R., Kyratzi, S., & Moulianitis, V. (2021). Technology enablers for the implementation of Industry 4.0 to traditional manufacturing sectors: A review. Computers in Industry, 125, 103390.
9. Kim, J. H. (2017). A review of cyber-physical system research relevant to the emerging IT trends: industry 4.0, IoT, big data, and cloud computing. Journal of industrial integration and management, 2(03), 1750011.
10. Kumar, K., Zindani, D., & Davim, J. P. (2019). Industry 4.0: developments towards the fourth industrial revolution. Cham, Switzerland: Springer.
11. Moshiri, M., Charles, A., Elkaseer, A., Scholz, S., Mohanty, S., & Tosello, G. (2020). An industry 4.0 framework for tooling production using metal additive manufacturing-based first-time-right smart manufacturing system. Procedia CIRP, 93, 32-37.
12. Peres, R. S., Jia, X., Lee, J., Sun, K., Colombo, A. W., & Barata, J. (2020). Industrial artificial intelligence in industry 4.0-systematic review, challenges and outlook. IEEE access, 8, 220121-220139.
13. Revathy, G., Selvakumar, K., Murugapriya, P., & Ravikumar, D. (2022). Smart manufacturing in Industry 4.0 using computational intelligence. In Artificial Intelligence for Internet of Things (pp. 31-48). CRC Press.anufacturing companies and broader: An overview. DAAAM International Scientific Book, 81-98.
14. Sahoo, S., & Lo, C. Y. (2022). Smart manufacturing powered by recent technological advancements: A review. Journal of Manufacturing Systems, 64, 236-250.
15. Singh, A., Jadhav, A., & Singh, P. AI Applications in Production. Industry 4.0, Smart Manufacturing, and Industrial Engineering, 139-161.
16. Trstenjak, M., & Cosic, P. (2017). Process planning in Industry 4.0 environment. Procedia Manufacturing, 11, 1744-1750.
17. Wang, J., Ma, Y., Zhang, L., Gao, R. X., & Wu, D. (2018). Deep learning for smart manufacturing: Methods and applications. Journal of manufacturing systems, 48, 144-156.
18. Garg, P., Dixit, A., & Sethi, P. (2019). Wireless sensor networks: an insight review. International Journal of Advanced Science and Technology, 28(15), 612-627.
19. Upadhyay, D., Garg, P., Aldossary, S. M., Shafi, J., & Kumar, S. (2023). A linear quadratic regression-based synchronised health monitoring system (SHMS) for IoT applications. Electronics, 12(2), 309.
20. Beniwal, S., Saini, U., Garg, P., & Joon, R. K. (2021). Improving performance during camera surveillance by integration of edge detection in IoT system. International Journal of E-Health and Medical Communications (IJEHMC), 12(5), 84-96.
21. Raj, G., Verma, A., Dalal, P., Shukla, A. K., & Garg, P. (2023). Performance comparison of several LPWAN technologies for energy constrained IOT network. International Journal of Intelligent Systems and Applications in Engineering, 11(1s), 150-158.
22. Gautam, V. K., Gupta, S., & Garg, P. (2024, March). Automatic Irrigation System using IoT. In 2024 International Conference on Automation and Computation (AUTOCOM) (pp. 100-103). IEEE.
23. Chauhan, S., Singh, M., & Garg, P. (2021). Rapid forecasting of pandemic outbreak using machine learning. Enabling Healthcare 4.0 for Pandemics: A Roadmap Using AI, Machine Learning, IoT and

ISBN: 978-93-343-1044-3

24. Garg, P., Pranav, S., & Prerna, A. (2021). Green Internet of Things (G-IoT): A Solution for Sustainable Technological Development. In Green Internet of Things for Smart Cities (pp. 23-46). CRC Press.
25. Nanwal, J., Garg, P., Sethi, P., & Dixit, A. (2021). Green IoT and Big Data: Succeeding towards Building Smart Cities. In Green Internet of Things for Smart Cities (pp. 83-98). CRC Press.
26. Beniwal, S., Saini, U., Garg, P., & Joon, R. K. (2021). Improving performance during camera surveillance by integration of edge detection in IoT system. International Journal of E-Health and Medical Communications (IJEHMC), 12(5), 84-96.
27. Magoo, C., & Garg, P. (2021). Machine learning adversarial attacks: A survey beyond. Machine Learning Techniques and Analytics for Cloud Security, 271-291.
28. Gupta, S., & Garg, P. (2023). 14 Code-based post-quantum cryptographic technique: digital signature. Quantum-Safe Cryptography Algorithms and Approaches: Impacts of Quantum Computing on Cybersecurity, 193.

ISBN: 978-93-343-1044-3